Fault Diagnosis of Induction Motor Based on Decision Trees and Adaptive Neuro-fuzzy Inference

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This paper presents a fault diagnosis method based on adaptive neuro-fuzzy inference system (ANFIS) in combination with decision trees. Classification and regression tree (CART) which is one of the decision tree methods is used as a feature selection procedure to select pertinent features from data set. The crisp rules obtained from the decision tree are then converted to fuzzy if-then rules that are employed to identify the structure of ANFIS classifier. The hybrid of back-propagation and least squares algorithm are utilized to tune the parameters of the membership functions. In order to evaluate the proposed algorithm, the data sets obtained from vibration signals and current signals of the induction motors are used. The results indicate that the CART-ANFIS model has potential for fault diagnosis of induction motors.

Key Words: Fault Diagnosis; Induction Motors; Feature Selection; Adaptive Neuro-fuzzy Inference; Decision Trees

1. Introduction

Induction motors are the workhorse of many different industrial applications due to their ruggedness and versatility. Although the induction motors are well constructed and robust, the possibility of faults is inherent due to stresses involved in the conversion of electrical to mechanical energy and vice versa. The faults of induction motors may not only cause the interruption of product operation but also increase costs, decrease product quality and effect safety of operators. Early detection of incipient faults can minimize breakdown and reduces maintenance time. Furthermore, the availability and reliability of machines will be also increased. Consequently, fault diagnosis for detection of faults in induction motors has been the subject of considerable research in recent years to avoid the stoppage of product operation. For increased productivity and safety reason, there has been an increasing demand for automated predictive maintenance and fault diagnosis system.

The most common faults of induction motors are bearing failures, stator phase winding failures, broken rotor bar or cracked rotor end-rings and air-gap irregularities (Acosta et al., 2006). Different approaches for motors incipient fault detection and diagnosis have successfully been proposed (Yang and Kim, 2006; Satish and Samar, 2005; Yang et al., 2004; Casimir et al., 2006; Widodo et al., 2007; Benbouzid and Nejjari, 2001). Most of these techniques involve vibration analysis and stator current analysis because they are easy to measure, high accuracy and reliability. Most of the current research works in motor incipient fault detection and diagnosis focused on integrating two or more intelligent techniques to obtain a hybrid model to utilize the excellence property and capability of individual classifier.

Artificial neural networks (ANNs) have been proven as a reliable technique to diagnose the condition of a motor and have good learning capability. However, ANNs are not interpretable and understandable, i.e. they are incapable of explaining a particular decision to the user in a human-comprehensible form. Fuzzy logic is another method, which has been used for fault detection and diagnosis (Benbouzid and Nejjari, 2001). It has the ability of modeling human knowledge in a form of if-then rules using easily understandable linguistic term. It has the capability of transforming linguistic and heuristic terms into numerical values for use in complex machine computation via fuzzy rules and membership functions. The if-then rules as well as the initial parameters of membership functions are normally prepared by an expert. Thus, fuzzy logic requires fine-turning in order to obtain acceptable rule base and optimize parameters for available data (Shukri et al., 2004). The individual problems from fuzzy logic or ANN alone can be solved by the integration of both methods and has been applied for motor fault diagnosis (Goode and Chow, 1995).

The adaptive neuro-fuzzy inference system (ANFIS) (Jang, 1993) is a specific kind of neuro-fuzzy classifier approach which integrates the ANNs adaptive capability and the fuzzy logic qualitative approach. ANFIS have been successfully applied for automated fault detection and diagnosis of induction machines (Shukri et al., 2004; Altug et al., 1999). Recently, ANFIS and its combination with other methods were also employed as an enhanced tool for fault classification. Some examples of the combined algorithms are ANFIS with genetic algorithms (Lei et al., 2007) and ANFIS with wavelet transform (Lou and Loparo, 2004) for bearing fault diagnosis. ANFIS has been applied in classifying the faults of induction motor with variable driving speed (Ye et al., 2006).

The data obtained from measurements is normally high dimension and has a large amount of redundant features. If the data is directly inputted into the classifier, the performance will be significantly decreased. Feature extraction and selection have been utilized for reducing the dimension of data by selecting important features wherein feature extraction means and transforming the existing features into a lower dimensional space (Yang et al., 2006). Nevertheless, each feature set contains many redundant or irrelevant features as well as salient features in feature space after the feature extraction has been done. Consequently, there is a need for feature selection procedure to select minimum features which can characterize the machine conditions from the whole feature set (Lei et al., 2007).

In this study, decision tree is utilized as feature selection procedure to remove irrelevant features for the purpose of reducing the amount of data needed to achieve good learning, classification accuracy, compact and easily understood knowledge-base, and a reduction in computational time (Kumar et al., 2005). It involves an integrated method which combines classification and regression trees (CART) and ANFIS for use of fault diagnosis of induction motors. The proposed approach consists of two stages. First, the CART is performed as a feature selection tool to obtain the valuable features and identifies the structure of classifier in the next iterative step. Second, the ANFIS classifier is used to diagnose the faults of induction motors wherein the parameters of membership functions which are tuned throughout the learning process.

2. Materials and Method

2.1 Classification and regression trees (CART)

CART algorithm (Breiman et al., 1984) is similar to other ones used in decision tree induction such as ID3 and C4.5 (Quinlan, 1986). One of the major distinctions is that CART induces strictly binary trees through a process of binary recursively partitioning of feature space of a data set (Jang et al., 1996). The trees produced by CART also consist of internal nodes (with two children) and terminal nodes or leaf nodes (without children). Each internal node is associated with a decision function to indicate which node to visit next, whilst each terminal node shows the output of a given input vector that leads the visit to this node (Sugeno and Kang, 1988). The decision tree shown in Fig. 1 evidently classifies the input space into four mutually exclusive rectangular regions which are assigned a labeled class. As in ID3 or C4.5, CART extensively builds the tree by using the data set of already classified instances which is called training set, and then prunes the tree back based on a minimum cost-complexity principle. The first phase is called *tree building*, and the other is *tree pruning*.

Fig. 1 Decision tree (Jang, 1994)

2.1.1 Tree building

The initial state of a decision tree is the root node (the first internal node) which assigned all the examples of the training set. If all the examples belong to the same class, then no further decisions need to be made to partition the examples and the solution is completed. Conversely, if the examples at this node belong to two or more classes, a test is made at the node that will result in a split and the training set is then divided into two sub-spaces. The process is recursively repeated for each of the new terminal node until a completely discriminating tree is obtained.

The test at internal nodes is determined based upon a measure of impurity to select which feature is selected and which threshold value is chosen. The best known measure of impurity for CART is entropy impurity given by,

$$E(t) = -\sum_{j=1}^{\#class} p(w_j \mid t) \log p(w_j \mid t) \tag{1}$$

where $E(t)$ is the entropy impurity at node t, $p(w_j|t)$ is the fraction of patterns at node t that belongs to class w_j.

The optimal splitting value s^* at node t is chosen from a set of all splitting candidates S so that the drop of impurity is maximized as

$$\Delta E\left(s^*, t\right) = \max_{s \in S} \Delta E\left(s, t\right) \tag{2}$$

where $\Delta E(s,t)$ is the drop of impurity given by

$$\Delta E(s,t) = E(t) - p_L E(t_L) - p_R E(t_R) \tag{3}$$

where t_L and t_R are left and right branch nodes, $E(t_L)$ and $E(t_R)$ are the impurities of the left and right branch nodes, p_L and p_R are the fraction of patterns at node t, respectively.

2.1.2 Tree pruning

The tree obtained by preceding building phase is biased toward the training data set (Jang et al., 1996) and may have a large number of branches which substantially increase the tree's complexity whilst they do not yield higher accuracy if resulting from noisy data. It is therefore necessary to prune the tree to improve the accuracy of classifier and to overcome the familiar over-fitting problem. The method for pruning in CART is based on the principle of minimum cost-complexity. Let T_{max} denotes a wholly expanded tree that is grown in building phase, the cost-complexity measure $E_\alpha(T)$ of sub-tree $T \subset T_{\max}$ is defined as:

$$E_\alpha(T) = E(T) - \alpha\left|\tilde{T}\right| \tag{4}$$

where $|\tilde{T}|$ is the number of terminal nodes in T and α is a complexity parameter.

The general process for pruning tree is executed as following steps:

Step 1: Beginning at the internal node t which is an upward terminal node of a tree T.

Step 2: Calculating the value of α, and denote by α_t, that makes T-T_t as the next minimizing tree for each internal node t, where α_t is given by

$$\alpha_t = \frac{E(t) - E(T_t)}{|\tilde{T}_t| - 1} \tag{5}$$

Step 3: Finding the minimal α_t and choosing T-T_t as the next minimizing tree.

Step 4: Repeating the process until the optimum-size tree is achieved by using an independent testing data set or performing cross-validation.

The resulting decision tree is an easy representation of the nonlinear input-output mapping. Furthermore, it is also easy for generating decision rules. For instance, the decision tree shown in Fig. 1 is equivalent to a set of crisp rules,

$$\begin{aligned} &\text{If } x > a \text{ and } y > b \text{ then } z = f_1 \\ &\text{If } x > a \text{ and } y \le b \text{ then } z = f_2 \\ &\text{If } x \le a \text{ and } y > c \text{ then } z = f_3 \\ &\text{If } x \le a \text{ and } y \le c \text{ then } z = f_4 \end{aligned} \tag{6}$$

Those crisp rules and thresholds are utilized to define the structure of neuro-fuzzy classifier and will be briefly described in the next section. However, the discontinuities at the decision boundaries are crisp and lead to large output variations for small changes in input features when such features are closed to decision boundaries.

2.2 Adaptive neuro-fuzzy inference system (ANFIS)

2.2.1 Architecture of ANFIS based on CART

The ANFIS architecture is an integration of fuzzy logic and neural network algorithm (Jang, 1994; Jang et al., 1996) which utilize the learning abilities of neural networks with human knowledge representation abilities of fuzzy systems.

In order to present the ANFIS architecture based on CART, crisp rules (6) in the previous section are considered. Assuming any input vector (x, y) is given, only one rule out of four will be fired at full strength whilst the other three rules will not be activated and the output is solely determined by the fired rule. Furthermore, the crisp sets reduce the computation burden in constructing the tree using CART, but it also gives undesired discontinuous boundaries as mentioned above. This problem can be solved by using fuzzy sets that can smooth out the discontinuities at each split. Fuzzy sets, therefore, are used to represent the premise part of the rule set in Eq. (6). This equation is converted into a set of fuzzy rules of either zero-order (when f_i's are constant) or first order (when f_i's are linear equations). Assuming that a first-order Sugeno fuzzy model (Sugeno and Kang, 1988) is considered, the crisp rules in Eq. (6) can be expressed as

$$\begin{aligned}
&\text{Rule 1: If } x > a \text{ and } y > b \text{ then } z = f_1 = p_1x + q_1y + r_1\\
&\text{Rule 2: If } x > a \text{ and } y \le b \text{ then } z = f_2 = p_2x + q_2y + r_2\\
&\text{Rule 3: If } x \le a \text{ and } y > c \text{ then } z = f_3 = p_3x + q_3y + r_3\\
&\text{Rule 4: If } x \le a \text{ and } y \le c \text{ then } z = f_4 = p_4x + q_4y + r_4
\end{aligned} \tag{7}$$

where x and y are the inputs, f_i are the outputs within the fuzzy region specified by the fuzzy rule, p_i, q_i, and r_i are the design parameters that are determined during the learning process.

Fig. 2 ANFIS architecture of first-order Sugeno fuzzy model

The ANFIS architecture to implement these rules consists of five layers as shown in Fig. 2. In this architecture, circles indicate fixed nodes, while squares indicate adaptive nodes. Nodes within the same layer perform identical functions as detailed below.

Layer 1: All the nodes are adaptive nodes. The outputs of this layer are the fuzzy membership grade of the inputs, which are given by:

$$O_i^1 = \mu_{x*d}(x) \tag{8}$$

$$O_i^1 = \mu_{x*d}(y) \tag{9}$$

where d is decision boundaries, and $\mu_{x*d}(x)$ and $\mu_{x*d}(y)$ can adopt any fuzzy membership function. For instance, the statement $y > c$ can be represented as a fuzzy set characterized by either the sigmoid membership function with one parameter α (Jang et al., 1996):

$$\mu_{y>c}(y;\alpha) = sig(y;\alpha,c) = \frac{1}{1+\exp[-\alpha(y-c)]} \tag{10}$$

or the extended sigmoid membership function with two parameters: α and γ

$$\mu_{y>c}(y;\alpha,\gamma)=sig(y;\alpha,c,\gamma)=\begin{cases}0 & if\quad y\le c-\alpha\\ \frac{1}{2}\left[\frac{y-(c-\alpha)}{\alpha}\right]^{2\gamma} & if\quad c-\alpha<y\le c\\ 1-\frac{1}{2}\left[\frac{c+\alpha-y}{\alpha}\right]^{2\gamma} & if\quad c<y\le c+\alpha\\ 1 & if\quad c+\alpha<y\end{cases} \tag{11}$$

where α, γ, c are the modifiable parameters governing the shape of the membership functions. Parameters in this layer are referred to as premise parameters.

Layer 2: The nodes are fixed nodes denoted as Π, indicating that they perform as a simple multiplier. Each node in this layer calculates the firing strengths of each rule via multiplying the incoming signals and sends the product out. The outputs of this layer can be represented as

$$O_i^2 = w_i = \mu_i(x)\mu_i(y), \quad i = 1,\ 2, 3 \text{ and } 4 \tag{12}$$

Layer 3: The nodes are also fixed nodes. They are labeled with *N*, indicating that they play a normalization role to the firing strengths from the previous layer. The *i*-th node of this layer calculates the ratio of the *i*-th rule's firing strength to the sum of all rules' firing strengths:

$$O_i^3 = \overline{w}_i = \frac{w_i}{\sum_{i=1}^{4} w_i} = \frac{w_i}{w_1 + w_2 + w_3 + w_4} \tag{13}$$

Note that this layer is not needed if the constraints: (a) $\mu_{x>a}(x)+\mu_{x\le a}(x)=1$ and (b) multiplication is used as the *T*-norm operator to calculate each rule's firing strength, with the summation over each rule's firing strength is always equal to one.

Layer 4: The nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial. Thus, the outputs of this layer are given by:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i), \quad i = 1, 2, 3 \text{ and } 4 \tag{14}$$

Layer 5: There is only single fixed node labeled with Σ. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by

$$O_i^5 = \sum_{i=1}^{4} \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{15}$$

Thus we have constructed an adaptive network that has exactly the same function as a Sugeno fuzzy model.

2.2.2 Learning algorithm of ANFIS

The task of learning algorithm for ANFIS architecture is to tune all the modifiable parameters, namely premise parameters {α, γ, c} and consequent parameters {p_i, q_i, r_i}, to make the ANFIS output matches the training data. The least squares method can be easily used to identify the optimal values of these parameters. When the premise parameters are not fixed, the search space becomes larger and convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve the problem. The hybrid algorithm is composed of a forward pass and a backward pass. In the forward pass, the least squares method is used to optimize the consequent parameters with the fixed premise parameters. Once the optimal consequent parameters are found, the backward pass commences immediately. In the back pass, the gradient descent method is used to adjust the premise parameters corresponding to the fuzzy sets in the input domain, whilst the consequent parameters remain fixed. This procedure is repeated until either the squared error is less than a specified value or the maximum number of training epoch is encountered.

3. Proposed system fault diagnosis

In this work, the vibration signals and current signals are utilized for detecting the faults of induction motors. The proposed system consists of four procedures as in Fig.3: data acquisition, feature calculation, feature reduction and fault classification which are specifically explained in the next section. In this section, the summary role of each procedure is described as follow:

Data acquisition: this procedure is used to attain the vibration signals and current signals. Furthermore, data processing is also carried out.

Feature calculation: the most significant features are calculated by using statistical feature parameters from time domain and frequency domain.

Feature reduction: the CART algorithm is used to select the salient features from the whole feature set.

Fault classification: The data obtained from feature reduction procedure is split into two data sets: training and testing data. Training data is employed to build the model whilst testing data is for validating the model. The results indicate the accuracy of classification.

Fig. 3 Proposed system for fault diagnosis

4. Results and discussion

4.1 Data acquisition

To validate CART-ANFIS model, experiment was carried out using a test-rig which consists of a motor, pulleys, belt, shaft and fan with changeable blade pitch angle that represents the load. The load can be changed by adjusting blade pitch angle or the number of blades. Six induction motors of 0.5 kW, 60 Hz, 4-pole were used to create data. One of the motors with good condition (healthy) is used for comparison with faulty motors. The others are faulty motors, with rotor unbalance, broken rotor bar, phase unbalance, bearing outer race fault, bowed rotor, and adjustable eccentricity motor, as shown in Fig. 4. The conditions of faulty motors are described in Table 1.

Fig. 4 Faults on the induction motors
Table 1 The description of faulty motors
Fig. 5 Vibration and current signals of each fault condition

For acquiring data from test rig, three AC current probes and three accelerometers were used to measure the stator current of the three-phase power supply and vibration signal in the horizontal, vertical, axial directions for evaluating the fault diagnosis system, respectively. The maximum frequency of the signal was 3 kHz, with 16,384 sampled data and giving a measured time of 2.133 s. The time waveform of vibration and stator current signals are shown in Fig. 5. From the vibration signals, it can be seen that there are difference between the waveforms of a normal, rotor unbalance, rotor bar broken and phase unbalance, which show approximate sine waves with frequency corresponds to the running speed. The characteristics of misalignment waveforms are sinusoidal with one or two clear cycles per revolution. There are many impacts in bowed rotor and faulty bearing waveforms. For stator current signals, the differences are not visible among these faults from time waveforms since the main component is line frequency and fault signals are modulated or riding on the sine wave of line frequency (60 Hz).

4.2 Feature calculation

The measured signals after being obtained from the experiment were calculated to obtain the most significant features by feature calculation. The accuracy of feature calculation is of substantial importance since it directly affects the final diagnosis results. In this paper, the feature calculation using statistical feature parameters from time domain and frequency domain was used. Sixty-three (63) features in total are calculated from 10 feature parameters of time domain. These parameters are mean, RMS, shape factor, skewness, kurtosis, crest factor, entropy error, entropy estimation and histogram of upper and lower limits. And three parameters from frequency domain (RMS frequency, frequency center and root variance frequency) using the three direction vibration signals and three-phase current signals. The total number of feature parameters is shown in Table 2. The data sets of the features have 270 samples. In each operating condition, 20 samples are employed for training process and 10 samples for testing. The detailed descriptions of those data sets are shown in Table 3.

Table 2 Feature parameters
Table 3 Descriptions of data sets

4.3 Feature selection and classification

A decision tree grows wholly based on training data sets and then prunes the tree back to give the final tree. Figs. 6 and 7 depict the trees corresponding to the data set of features obtained from vibration signals and current signals, respectively. Obviously, the feature appearing in root node of the trees is the most important one. The other features in remaining nodes appear in descending order of importance. It is to be emphasized which only features that contribute to the classification appear in the decision tree and the others do not. Features, which have less discriminating capability, can be consciously discarded by deciding on the threshold. From that, a number of features are strikingly diminished and only 4 features (x_2, x_5, x_{15} and x_{23}) of vibration signal and 7 features (x_2, x_5, x_6, x_8, x_{11}, x_{15} and x_{19}) of current signal are remained.

The reduction of features will decrease the burden of computation for ANFIS classifier in the next step. Furthermore, the structure of ANFIS classifier can be defined based on the crisp rules and boundary values of the decision trees.

Fig. 6 Decision tree of features obtained from vibration signals
Fig. 7 Decision tree of features obtained from current signals
Fig. 8 Topology of ANFIS architecture for vibration signals

In order to implement the fault diagnosis of induction motors by using ANFIS classifier, the structure identification for classifier is antecedently defined. This structure includes fuzzy rule set and membership functions. The fuzzy rule set is also crisp rule set of decision tree that has been fuzzyfied. Bell-shaped membership functions, from which the initial parameters are determined based on boundary values, are chosen for our classifiers. For instance, the topology of ANFIS architecture designed using MATLAB software package with fifteen fuzzy rules for vibration signal data set is shown in Fig. 8. In this figure the number of nodes in each layer, the number of fuzzy rules and other meaningful information can be seen.

The system parameters and the chosen membership functions are automatically adjusted during the learning process. The convergence of the root mean squared (RMS) error is utilized to evaluate the learning process. If the decreasing rate of the RMS error as well as the performance is not significant, the learning process can be terminated. In Fig. 9, the RMS error decreased to 0.087 after 800 training epochs for the vibration signal data set which meant the network had learned the training data very well. In other words, the premise parameters of the membership functions corresponding to the inputs were changed for the sake of network convergence according to the given training samples. The membership function of each input parameter was divided into three regions, namely small, medium and large. Fig. 10 shows the initial (before training) and final (after training) membership functions of the four input parameters, using the generalized bell-shaped membership function. From this figure, it shows that changes of the final membership functions of input 2 (x_5) and input 3 (x_{15}) are similar while input 1 (x_2) and input 4 (x_{23}) have changed.

Fig. 9 The network RMS error convergence curve
Fig. 10 Bell-shaped membership functions for vibration signals

The classification results are calculated using a ten-fold cross-validation evaluation where the data set to be evaluated is randomly partitioned so that 180 samples are used for training and 90 samples are used for testing. The process is iterated with different random partitions and the results are averaged. The CART-ANFIS achieved 100% classification accuracy without any misclassification out of 180 samples of training data for vibration and current signals. After training, the CART-ANFIS was tested against the testing data. The confusion matrix showing the classification results of the CART-ANFIS created with 800 epochs of training cycle is given in Table 4. In confusion matrix, each cell contains the number of samples that was correctly classified corresponding to actual network outputs and desired outputs of vibration signals and current signals. For example, the number is shown as 10/7 in the first cell (the first column and the first row of confusion matrix) means that there were 10 outputs were belonged to class C1 and 7 outputs were belonged to class C1 for vibration signals and current signals, respectively. It is similar to the other cells in the diagonal of confusion matrix. The other cells that were not in the diagonal of confusion matrix indicate the misclassifications. For example, the cell being in the first column and the third row has the value as 0/1 shows that all subjects were correctly classified for vibration signals and one subject should have belonged to class C1 was classified as subjects of class C3.

The total classification accuracy for the test data was found as 91.11% with 8 misclassification out of 90 test samples for the vibration signal, while 76.67% with 21 misclassification out for the current signal.

The test performance of the classifier can be determined by the computation of statistical parameters such as sensitivity, specificity and total classification accuracy defined by:

Sensitivity: number of true positive decisions/number of actually positive cases.

Specificity: number of true negative decisions/number of actually negative cases.

Total classification accuracy: number of correct decisions/total number of cases.

The values of statistical parameters are given in Table 5. The CART-ANFIS model classified C1 to C9 subject in form of a/b which implies the accuracy of classification corresponding to vibration signals and current signals as follows: 100/70, 100/80, 70/90, 90/80, 80/70, 100/70, 90/70, 100/80 and 90/80% for vibration and current signals, respectively. Those values are obtained from the cells that are in the diagonal of confusion matrix. All of the data sets were classified with the accuracy of 91.11%/76.67% (total classification accuracy).

Table 4 The confusion matrix for CART-ANFIS of 800 epochs

Table 5 The value of statistical parameters

5. Conclusion

A combined classification and regression tree (CART) algorithm and adaptive neuro-fuzzy inference system (ANFIS) have been presented to perform fault diagnosis of induction motors. The implementation of CART-ANFIS based classifier requires two consecutive steps. Firstly, CART is utilized to select the relevant features in data set obtained from feature calculation part. The output of CART is decision tree that is employed to product the crisp if-then rule set. Secondly, the structure of ANFIS classifier is defined based on the obtained rules, which are fuzzyfied in order to avoid classification surface discontinuity. A hybrid algorithm is incorporated to tune the parameters fuzzy memberships. The classification results and statistical measures were used for evaluating the CART-ANFIS model. The total classification accuracy was 91.11% and 76.67% for vibration and current signals, respectively. The results indicate that the proposed CART-ANFIS model can be used in diagnosing induction motor faults.

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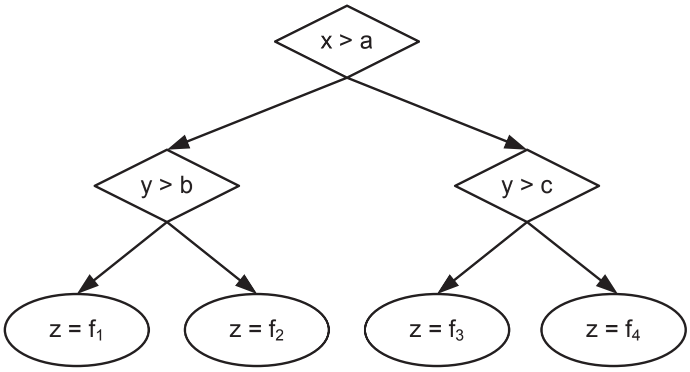
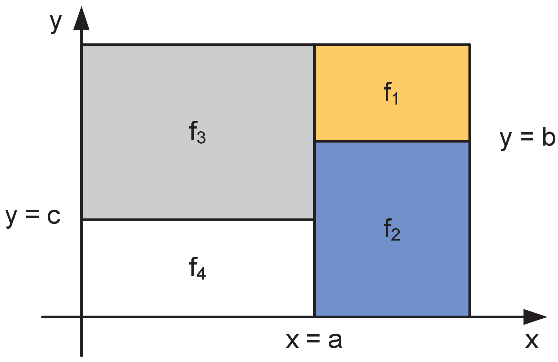


(a) Binary decision tree



(b) Feature space partitioning

Fig. 1 Decision tree (Jang, 1994)

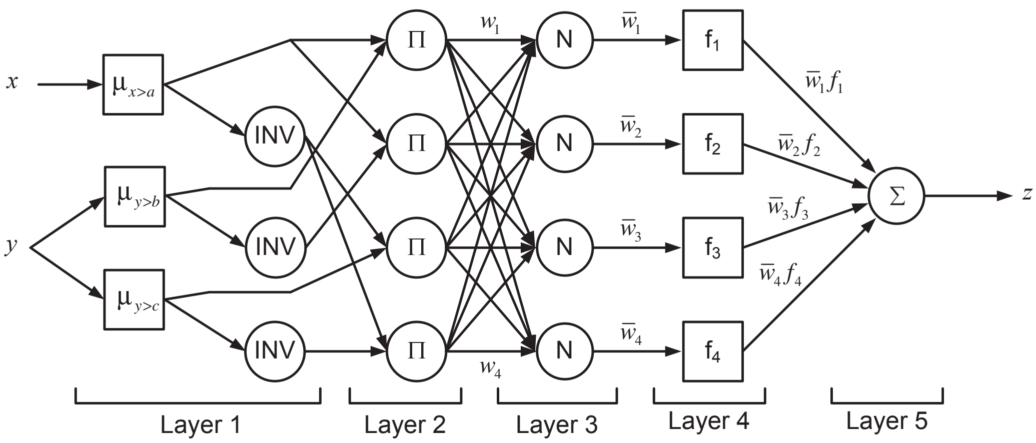


Fig. 2 ANFIS architecture of first-order Sugeno fuzzy model

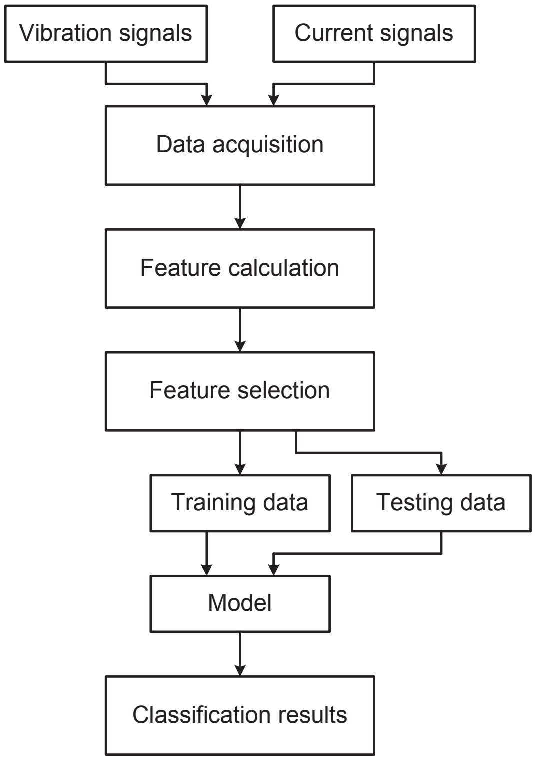


Fig. 3 Proposed system for fault diagnosis

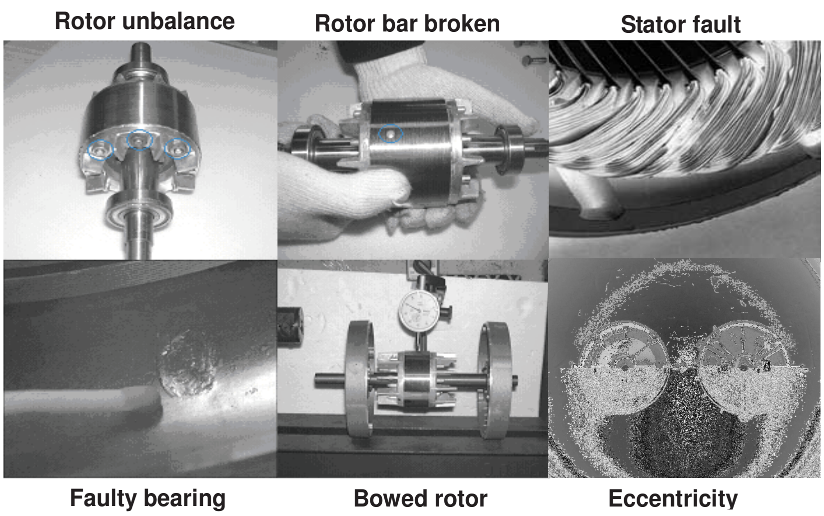


Fig. 4 Faults on the induction motors

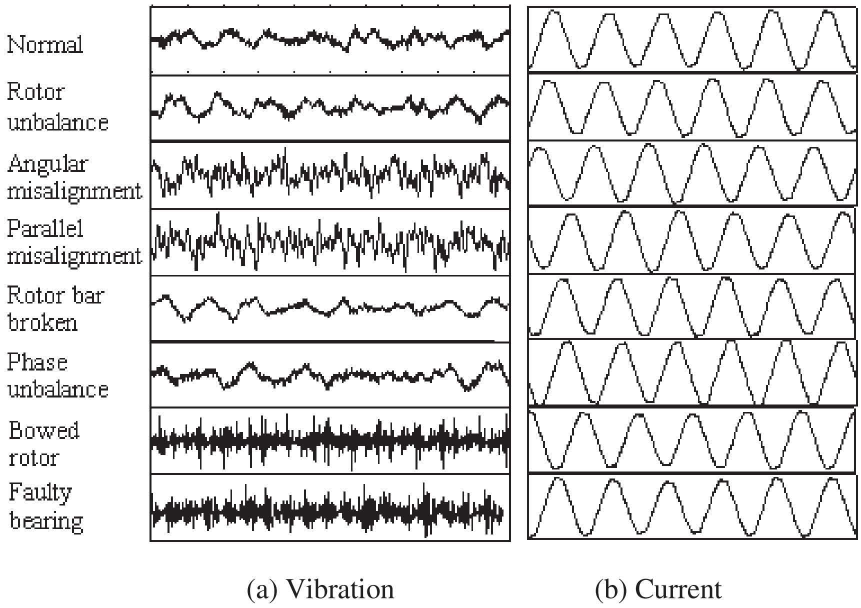


Fig. 5 Vibration and current signals of each fault condition

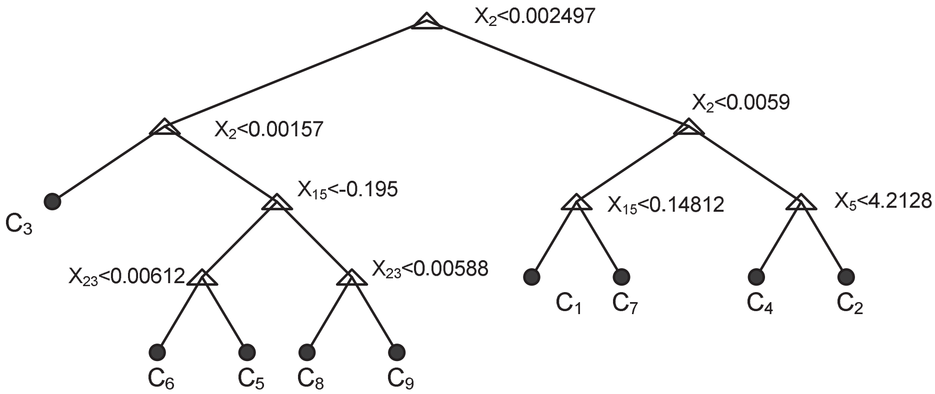


Fig. 6 Decision tree of features obtained from vibration signal

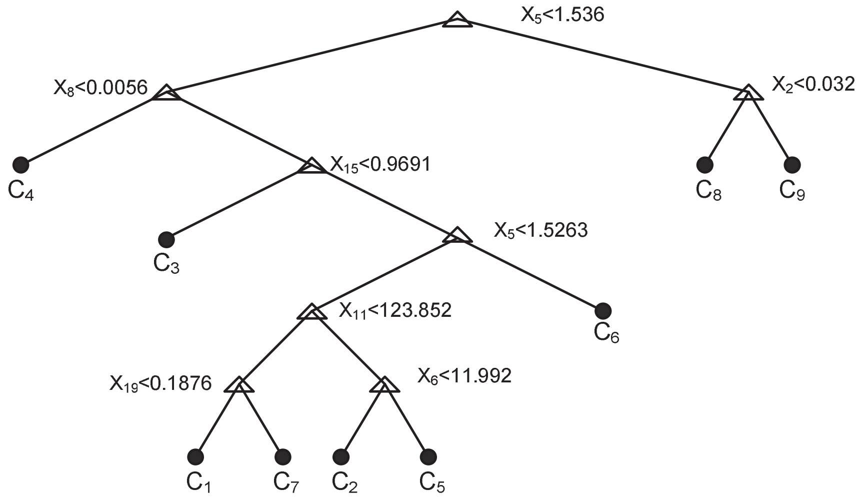


Fig. 7 Decision tree of features obtained from current signal

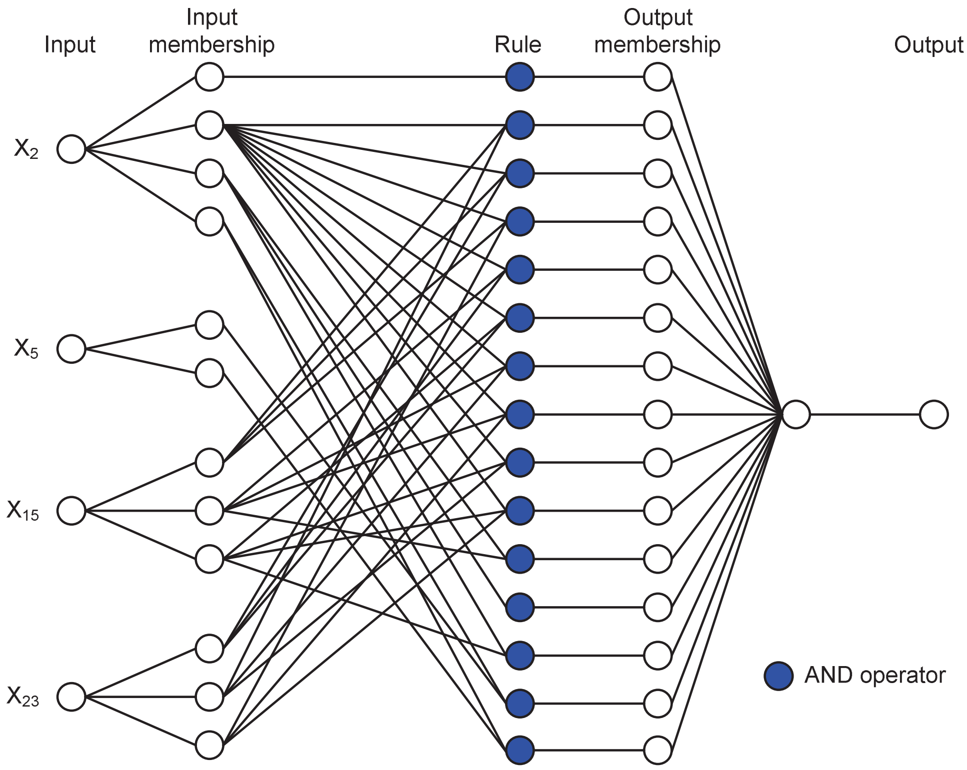


Fig. 8 Topology of ANFIS architecture for vibration signals

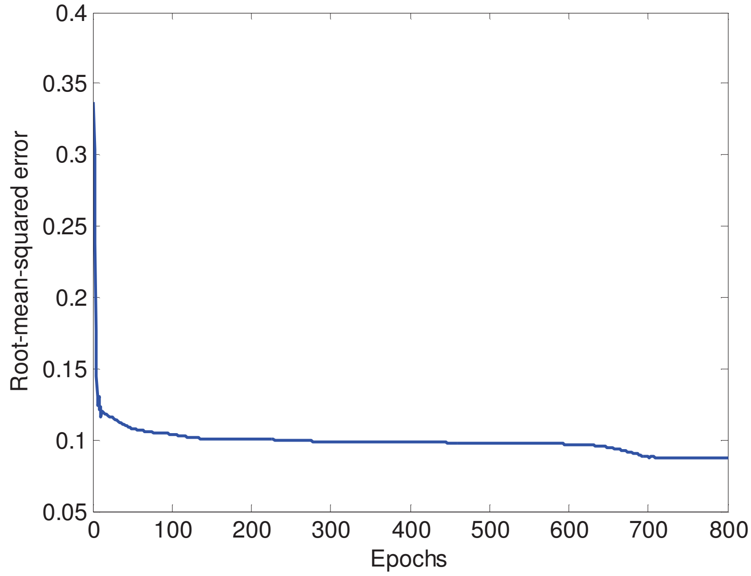
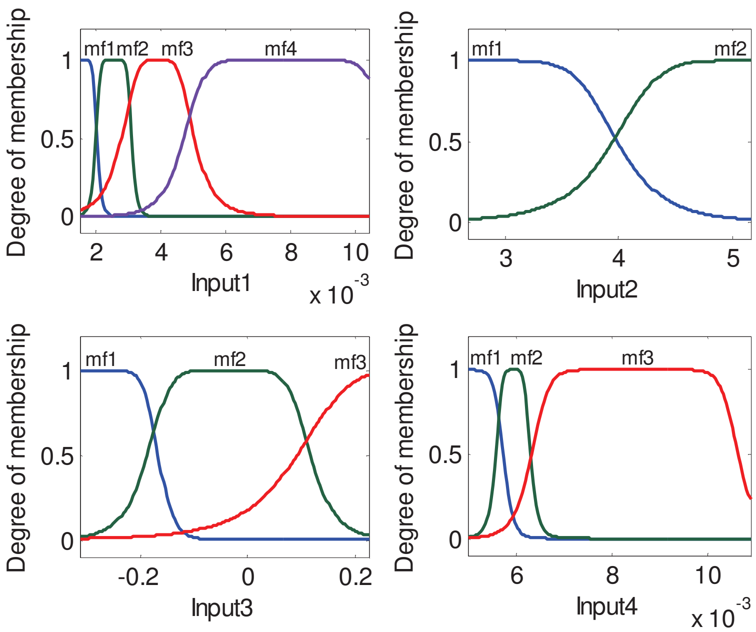
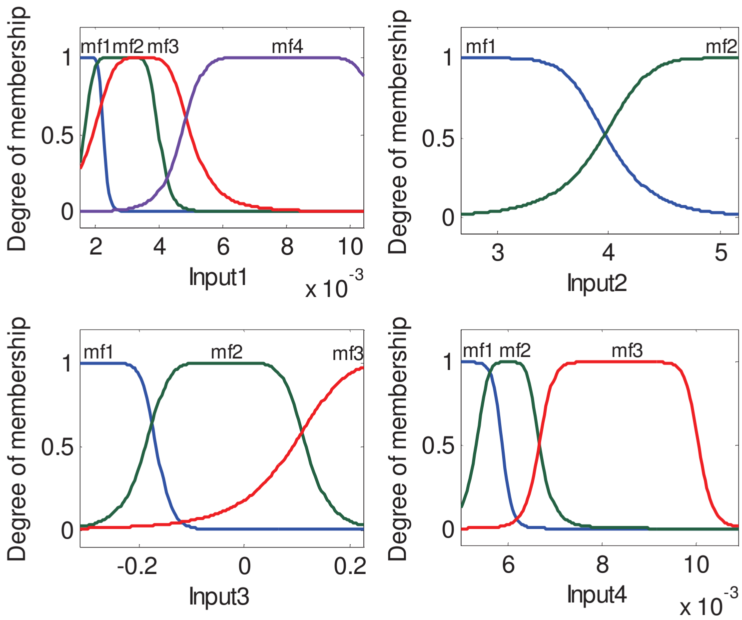


Fig. 9 The network RMS error convergence curve



(a) Initial (before training)



(b) Final (after training)

Fig. 10 Bell shaped membership functions for vibration signals

Table 1 The description of faulty motors

Fault condition	Fault description	Others
Broken rotor bar	Number of broken bar:12 ea	Total number of 34 bars
Bowed rotor	Max. shaft deflection: 0.075mm	Air-gap: 0.25mm
Faulty bearing	A spalling on outer raceway	#6203
Rotor unbalance	Unbalance mass on the rotor	8.4g
Eccentricity	Parallel and angular misalignments	Adjusting the bearing pedestal
Phase unbalance	Add resistance on one phase	8.4%

Table 2 Feature parameters

Signals	Position	Feature parameters	
		Time domain	Frequency domain
Vibration	Vertical	Mean	RMS variance frequency
	Horizontal	RMS	Frequency center
	Axial	Shape factor	Root variance frequency
Current	Phase A	Skewness	
	Phase B	Kurtosis	
	Phase C	Crest factor	
		Entropy error	
		Entropy estimation	
		Histogram lower	
		Histogram upper	

Table 3 Descriptions of data sets

Label of classification	Condition	Number of training samples	Number of testing samples
C1	Angular misalignment	20	10
C2	Bowed rotor	20	10
C3	Broken rotor bar	20	10
C4	Bearing outer race fault	20	10
C5	Mechanical unbalance	20	10
C6	Normal condition	20	10
C7	Parallel misalignment	20	10
C8	Phase unbalance (30°)	20	10
C9	Phase unbalance (50°)	20	10
Total samples		180	90

Table 4 The confusion matrix for CART-ANFIS of 800 epochs

Output/ desired	Confusion matrix (vibration/current signals)								
	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	10/7	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0
C2	0/0	10/8	0/0	1/0	1/0	0/0	1/1	0/1	0/0
C3	0/1	0/0	7/9	0/1	0/1	0/2	0/0	0/0	1/2
C4	0/0	0/0	0/0	9/8	0/1	0/0	0/1	0/1	0/0
C5	0/0	0/0	0/0	0/0	8/7	0/0	0/0	0/0	0/0
C6	0/0	0/0	0/0	0/0	0/0	10/7	0/0	0/0	0/0
C7	0/0	0/0	0/0	0/0	0/0	0/1	9/7	0/0	0/0
C8	0/2	0/2	1/1	0/1	1/0	0/0	0/0	10/8	0/0
C9	0/0	0/0	2/0	0/0	0/1	0/0	0/1	0/0	9/8

Table 5 The value of statistical parameters

Datasets label	Statistical parameters (vibration/current signals)		
	Sensitivity (%)	Specificity (%)	Total classification accuracy (%)
C1	100/70	100/100	91.11/76.67
C2	100/80	96.5/97.5	
C3	70/90	98.75/91.25	
C4	90/80	100/96.25	
C5	80/70	100/100	
C6	100/70	100/100	
C7	90/70	100/98.75	
C8	100/80	97.5/92.5	
C9	90/80	97.5/97.5	